Classification of wood surface texture based on Gauss-MRF Model

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Abstract: The basal theory of Gauss-MRF is expounded and 2–5 order Gauss-MRF models are established. Parameters of the 2–5 order Gauss-MRF models for 300 wood samples' surface texture are also estimated by using LMS. The data analysis shows that: 1) different texture parameters have a clear scattered distribution, 2) the main direction of texture is the direction represented by the maximum parameter of Gauss-MRF parameters, and 3) for those samples having the same main direction, the finer the texture is, the greater the corresponding parameter is, and the smaller the other parameters are; and the higher the order of Gauss-MRF is, the more clearly the texture is described. On the condition of the second order Gauss-MRF model, parameter B1, B2 of tangential texture are smaller than that of radial texture, while B3 and B4 of tangential texture are greater than that of radial texture. According to the value of separated criterion, the parameter of the fifth order Gauss-MRF is used as feature vector for Hamming neural network classification. As a result, the ratio of correctness reaches 88%.
Keywords: Wood surface texture; Gauss-MRF; Feature parameter; Parameter estimation, Separation judgment; Classification
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Introduction

The natural texture has a complicated structure. Presently there has not been a standard to describe its feature. How to describe and classify natural textures is an important issue in the field of computer vision (Li and Liu 1998). The description of texture feature is divided into statistical method, structural method, and model method (Sheng 2000) It has been proved by practice that the statistical method represented by Gray Level Co-occurrence Matrix is suitable for dealing with the natural texture, but its feature parameter is unable to clearly indicate the geometrical feature of the texture and the computation work is too large. The random model method represented by Markov random field has a unique advantage in this aspect because the parameters produced by the method can describe the gathering characters of the texture in different directions and different patterns (Gong 1999), which is in good accordance with the sensory organ of human beings.

Classification of texture remains with pattern-recognition. Among those texture feature parameters, there exists both a dependent relation and a non-linear relation. Meanwhile, it involves an estimation issue of priori probability density. Therefore it is difficult to classify the texture with traditional Bayes decision theory (Bian *et al.* 2000). Being similar to the human brain in processing complicated non-linear information, the neural network brings about a vital force for pattern-recognition field, of which the most noticeable ones are BP neural network and competition neural network.

A method with Gauss-Markov Random Field to set up feature parameters of texture is put forward in this paper, and the natural texture of wood is classified with the competition neural network.

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Gauss-Markov Random Field

Markov Random Field (abbreviated as MRF) is the mathematics theory of random process description put forward by D. Geman and S. Geman in 1984. Its definition is as follows:

Let $S = (S_1, S_2, \ldots, S_N)$ be the position set in a 2D space, X be the random variable. The random event $(x_1, x_2, \ldots, x_N)$ can be expressed as $(X=\omega)$, $\omega \in \Omega$, Ω is the value space of random variable; ζ is the neighborhood system of the 2D space. All only and, $\omega \in \Omega$, $p(X=\omega) > 0$, we have

$$p\left(x_s \middle| x_r, r \neq s\right) = p\left(x_s \middle| x_r, r \in \xi\right) \tag{1}$$

For all S, ω holds, then {X} is a Markov random field. A 2D picture can be regarded as a Markov random field, which means that the gray level probability of any picture element in a picture field is decided by the gray level of picture element in its neighborhood system. And the overall probability of whole random field can be indicated by conditional probability distribution describing its local characters. When the noise of MRF neighborhood meets the Gauss distribution, a linear equation can be obtained which is expressed by a group of airspace element gray level, called Gauss-Markov Random Field model.

Gauss-Markov Random Field (Gauss-MRF) is a steady auto-regression course. The covariance matrix of Gauss-MRF is positively determined and the neighborhood system is symmetrical, with the parameters of the symmetrical neighborhood being equal. Expressing texture with Gauss-MRF, namely the gray level $y(s)$ of any point s in the picture is the function of neighborhood gray level in all direction, which can be shown in following condition probability form:

$$p(y(s) | all : y(s+r), r \in N) \tag{2}$$

Where, N is a symmetrical neighborhood with s (s is not included) being its center and r being its radius. The relation between the order of Gauss-MRF and the neighborhood system is shown in Figure 1.

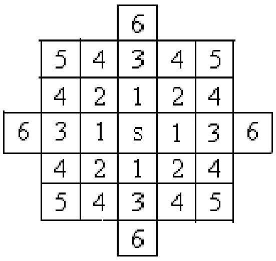

Fig. 1 The model of Gauss-Markov Random Field

Let S be the point set on $M \times M$ net, and $S = \{(\mathrm{i}, \mathrm{j}),\ 1 \le \mathrm{i}, \mathrm{j} \le \mathrm{M}\}$, the texture y(s), s$\in$S, S={(i, j), 1 ≤ i, j ≤M} is a Gauss random process of zero mean value. Then Gauss-MRF can be expressed with a linear equation including several unknown parameters.

$$y(s) = \sum_{r \in N_s} \theta_r [y(s+r) + y(s-r)] + e(s).. \tag{3}$$

Where, N_S is the Gauss-MRFneighborhood system of s, r the radius of neighborhood, θ_r the coefficient, and $e(s)$ the gauss noises array with a zero mean value. Since N is symmetrical, and $\theta_r = \theta_{-r}$, Equation (3) can be expressed as

$$y(s) = \sum_{r \in N_s} \theta_r [y_1(s+r)] + e(s) \tag{4}$$

Where, (s + r) is a point in a closed annular area S, for $s = (i, j), r = (k, l)$, we have

$$y_1(s+r) = \begin{cases} y_1(s+r) & \text{if} \quad \mathrm{s+r} \in \mathrm{S} \\ \mathrm{y}[(\mathrm{i+k-1}) \bmod (\mathrm{M+1}), (\mathrm{j+l-1}) \bmod (\mathrm{M+1}] & \text{if} \quad \mathrm{s+r} \notin \mathrm{S} \end{cases} \tag{5}$$

If Equation (5) is applied to every point in zone S, the M^2 equations with respect to {e(s)} and {y(s)} can be obtained (Gong 1999; Sheng 2000).

$$y(1,1) = \sum_{r \in N_s} \theta_r y_1((1,1) + r) + e(1,1) \qquad ,\ldots\ldots\ldots\ldots\ldots,$$

$$y(1, M) = \sum_{r \in N_s} \theta_r y_1((1, M) + r) + e(1, M)\ , \ldots,$$

$$y(M,1) = \sum_{r \in N_s} \theta_r y_1((M,1) + r) + e(M,1) \qquad ,\ldots\ldots,$$

$$y(M, M) = \sum_{r \in N_s} \theta_r y_1((M, M) + r) + e(M, M)$$

Expressed in the form of matrix, it becomes

$$y = Q^T \theta + e \tag{6}$$

Equation (6) is a linear model of Gauss-MRF, of which Q^T is the matrix about $y_1(s+r)$, and θ is the feature parameter vector of the model to be determined.

Gauss-Markov Random Field Model and Parameters Estimation

If the 2nd order Gauss-MRF model is adopted,

$$Q_s = \left| y_{s+r_1} + y_{s-r_1}, \cdots, y_{s+r_4} + y_{s-r_4} \right|^T \tag{7}$$

{r1, r2, r3, r4} = {(0,1), (1,0), (1,1), (1,-1)}, then θ is a four-dimensional vector, and $\theta = (\theta_1, \theta_2, \theta_3, \theta_4)^T$.

If the 3rd order Gauss-MRF model is adopted,

$$Q_s = \left| y_{s+r_1} + y_{s-r_1}, \cdots, y_{s+r_6} + y_{s-r_6} \right|^T \tag{8}$$

{r1, r2, r3, r4, r5, r6} = {(0,1), (1,0), (1,1), (1,-1), (0,2), (2,0)}, then θ is a (6D) six-dimensional vector, and $\theta = (\theta_1, \theta_2, \theta_3, \theta_4, \theta_5, \theta_6)^T$.

If the 4th order Gauss-MRF model is adopted,

$$Q_s = \left| y_{s+r_1} + y_{s-r_1}, \cdots, y_{s+r_{10}} + y_{s-r_{10}} \right|^T \tag{9}$$

{r1, r2, r3, r4, r5, r6, r7, r8, r9, r10}={(0,1), (1,0), (1,1), (1,-1), (0,2), (2,0), (1,2), (-1,2), (2,1), (-2,1)}, then θ is a (10D) ten-dimensional vector, and $\theta = (\theta_1, \theta_2, \theta_3, \theta_4, \theta_5, \theta_6, \theta_7, \theta_8, \theta_9, \theta_{10})^T$.

If the 5th order Gauss-MRFmodel is adopted,

$$Q_s = \left| y_{s+r_1} + y_{s-r_1}, \cdots, y_{s+r_{12}} + y_{s-r_{12}} \right|^T \tag{10}$$

{r1, r2, r3, r4, r5, r6, r7, r8, r9, r10, r11, r12} = {(0,1), (1,0), (1,1), (1,-1), (0,2), (2,0), (1,2), (-1,2), (2,1), (-2,1), (-2,2), (2,2)}, then θ is a (12D) twelfth-dimensional vector, and $\theta = (\theta_1, \theta_2, \theta_3, \theta_4, \theta_5, \theta_6, \theta_7, \theta_8, \theta_9, \theta_{10}, \theta_{11}, \theta_{12})^T$

Eqs. (11) and (12) can be solved by Estimating method of Least Mean Square as follows:

$$\hat{\theta} = (\sum_{s \in S_1} Q_s Q_s^T)^{-1} (\sum_{s \in S_1} Q_s y_s) \tag{11}$$

$$\hat{\sigma} = \frac{1}{N^2} \sum_{s \in S_1} (y_s - \hat{\theta}^T Q_s)^2 \tag{12}$$

where $\hat{\theta}$ is the consistent estimation of Gauss-MRF model parameters (Gong 1999; Sheng 2000); $\hat{\sigma}$ is the square error of parameter estimation.

When the order of neighborhood is low, there is a certain limitation to describe the feature of complicated pictures with Gauss-MRF. $\hat{\theta}$ can describe more complicated textures with high order Gauss-MRF.

Feature parameter collection and classification

Feature parameter collection and analysis

We chose 300 pictures (1:1) of radial texture and tangential texture samples of 4 common woods, *Pinus koraiensis, Larix gmelinii, Fraxinus mandshurica* and *Quercus mongolica*. The size of the sample is 12 cm ×12 cm, the resolution ratio is 512 ×

512 (Fig. 2). Gauss-MRF parameter estimation procedure was programmed with Matlab6.5, 2-5 order Gauss-MRF parameters were calculated.

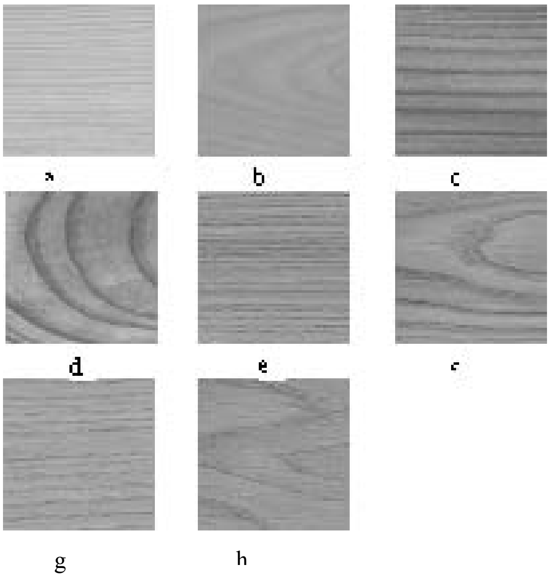

Fig. 2 The pictures of radial texture and tangential texture of four wood species

a is of radial-texture of *P .koraiensis*; b is tangential-texture of *P. koraiensis*; c is radial texture of *L. gmelinii*; d is of tangential-texture of *L.gmelinii*; e is radial-texture of *F. mandshurica*; f is tangential-texture of *F. mandshurica*; g is radial-texture of *Q. mongolica* ; h is tangential-texture of *Q. mongolica*.

In this paper, as space is limited, only the 2nd order Gauss-MRF model feature parameters B1–B4 of 24 wood samples are listed in Table 1 and Table 2. Parameter, B1, B2, B3, and B4, describe the texture feature in the direction of 0°, 45°, 90°, and 135°, respectively.

From Table 1 and 2, we can educe the following regulation of wood texture. 1) For a certain concrete sample, the maximum texture parameter's gathering direction is main texture direction; 2) For the samples whose main directions are the same, the finer and the clearer the texture is, the greater its corresponding parameter is, and the smaller the other parameters are. Since the sample direction of texture is mainly around 0°, B1 is the greatest; B1, B2 of tangential texture are smaller than that of radial texture, B3, B4 of tangential texture are greater than that of radial texture, respectively. Therefore it can be used as the basis to classify radial-texture and tangential-texture. In practice, however, a threshold value is necessary to be determined on the basis of a large number of samples.

In order to determine the validity of Gauss-MRFparameters of every order for describing wood surface texture feature, 300 samples was artificially divided into six texture types, 50 for each, and the mean value and square average of the corresponding parameters were calculated, as is shown in Figure 3. It showed that the Gauss-MRF parameters of different orders were marked different in different texture types. It is feasible to describe wood texture with these feature parameters. Obviously, the higher the order is, the more the parameters are, and the more particular the texture is described, but the operation amount will be also increased correspondingly.

Table1. The second rank Gauss-MRFparameters of radial texture

Sample	B1 (0º)	B2 (90º)	B3 (45º)	B4 (135º)
1. *P .koraiensis*	0.4732584	0.2470993	-0.10378	-0.116577
2. *P. koraiensis*	0.4803995	0.2515258	-0.129619	-0.102304
3 .*P. koraiensis*	0.4788409	0.2559477	-0.110502	-0.124283
4. *L. gmelinii*	0.4995179	0.3231366	-0.170195	-0.152455
5 .*L. gmelinii*	0.4933195	0.3467532	-0.165938	-0.174124
6.*L. gmelinii*	0.4938472	0.3614616	-0.203164	-0.152134
7. *F. mandshurica*	0.4979165	0.353452	-0.190948	-0.160427
8. *F. mandshurica*	0.4955053	0.3663765	-0.162626	-0.199276
9. *F. mandshurica*	0.4994605	0.3470714	-0.159778	-0.186764
10.*Q. mongolica*	0.4989654	0.3707962	-0.183878	-0.185881
11.*Q. mongolica*	0.499075	0.3343957	-0.172211	-0.161274
12 .*Q. mongolica*	0.497424	0.3631751	-0.191612	-0.168995

Table 2. The second rank Gauss-MRFparameters of tangential texture

Sample	B1 (0º)	B2 (90º)	B3 (45º)	B4 (135º)
1. *P. koraiensis*	0.4588136	0.2509415	-0.103155	-0.106618
2. *P. koraiensis*	0.4860764	0.2039888	-0.1158	-0.074266
3. *P. koraiensis*	0.4738804	0.1818294	-0.075555	-0.080157
4. *L.gmelinii*	0.4928261	0.2544015	-0.136343	-0.110896
5. *L. gmelinii*	0.498788	0.2733763	-0.131518	-0.140647
6. *L. gmelinii*	0.4844843	0.3396408	-0.147242	-0.176888
7. *F. mandshurica*	0.4939181	0.2921971	-0.124758	-0.1614
8. *F. mandshurica*	0.4978635	0.3419207	-0.199438	-0.140378
9. *F. mandshurica*	0.4985287	0.3194452	-0.142495	-0.175541
10. *Q. mongolica*	0.4989141	0.2748764	-0.148427	-0.12537
11.*Q. mongolica*	0.4951261	0.2662392	-0.095775	-0.165599
12.*Q. mongolica*	0.4977932	0.2638029	-0.156383	-0.105217

Feature parameters collection and the texture clustering

Although we had already calculated Gauss-MRF parameters of wood texture of 2nd to 5th order, which order's model parameters are best is still a question. From view point of pattern-recognition, we must use the separation criterion of texture classification to determine the feature vector of texture rather than only according to the difference of a single feature parameter variable (Bian *et al*. 2000). The classification separating creterion is defined as

$$J_d(x) = \frac{1}{2}\sum_{i=1}^{c} P_i \sum_{j=1}^{c} P_j \frac{1}{n_i n_j} \sum_{k=1}^{n_i} \sum_{l=1}^{n_j} (x_k^{(i)} - x_l^{(j)})^T (x_k^{(i)} - x_l^{(j)}) \tag{13}$$

Where C is the number of species, n_i and n_j the number of samples in a species, P_i and P_j the priori probability of the corresponding species, and $x_k^{(i)}$ and $x_l^{(j)}$ the parameters of a certain sample in species ωi and ωj. Let

$$m_i = \frac{1}{n_i}\sum_{k=1}^{n_i} x_k^{(i)} \tag{14}$$

$$m = \sum_{i=1}^{c} P_i m_i \tag{15}$$

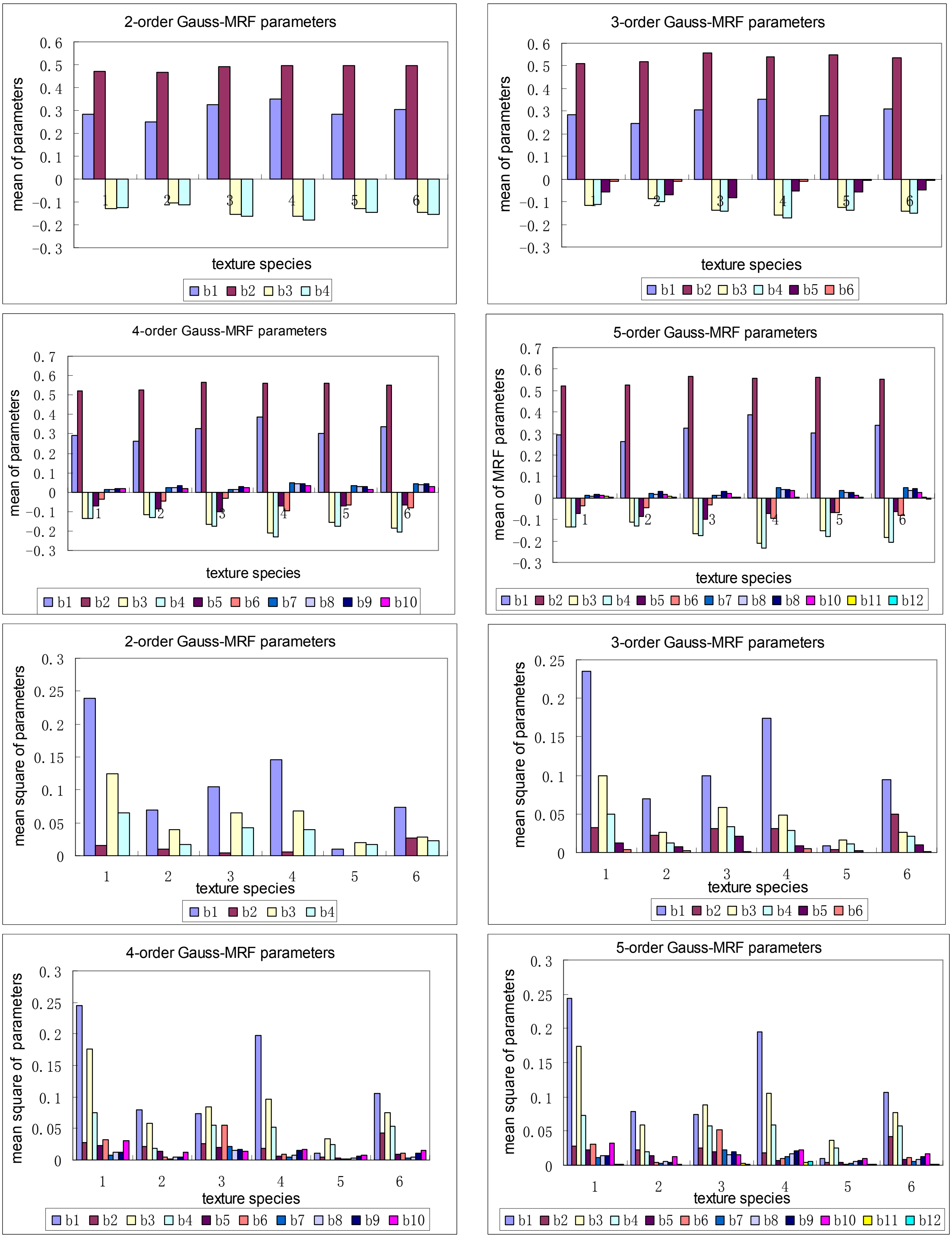

Fig. 3 The 2-5 orders of Gauss-MRFtexture parameters' average and square difference of six wood texture species

$$\tilde{S}_b = \sum_{i=1}^{c} P_i (m_i - m)^T (m_i - m) \quad (16)$$

$$\tilde{S}w = \sum_{i=1}^{c} P_i \frac{1}{n_i} \sum_{k=1}^{n_i} (x_k^{(i)} - m_i)(x_k^{(i)} - m_i)^T \quad (17)$$

Where m_i is a mean vector of all feature parameter in a species, m the population mean vector of all feature parameters for all species, $\tilde{S}_b$ the parameter distribution matrix of all species, and $\tilde{S}w$ the divergence matrix among all species. Then

$$J_d = tr(\tilde{S}w + \tilde{S}_b). \quad (18)$$

In Equation (18), the greater the J_d is , the easier the species is separated. The value of separation criterion is shown in Table 3 based on Equation (19).

Table 3. Separation criterion of 2-5 order Gauss-MRFtexture parameters of six wood texture species

Orders of Gauss-MRF	2nd order	3rd order	4th order	5th order
separation criterion	0.0058	0.0065	0.0115	**0.0121**

Table 3 proves that the separation criterion value of 5th order Gauss-MRF parameters is the maximum one in six kinds of wood texture, so, the 5th order Gauss-MRFparameters are the best one to be used as the feature vector for the texture classification.

In order to verify the validity of the texture parameters in classification, Hamming competition neural network is adopted to classify 300 wood texture pictures with B1–B12 of the 5th order Gauss-MRF parameters, the overall ratio of correctness is 88%, which can basically satisfy the requirement for automatic computer classification .

Conclusion

The research shows that, by using the Gauss-MRF model, 1) the description of the wood surface texture becomes the estimation of texture parameters; 2) the feature of wood surface texture described by Gauss-MRF model has a clear physics meaning, the gathering direction of the maximum texture parameter is the main direction of textures; 3) for those samples with the same main direction, the finer and the clearer of the texture is, the greater the corresponding parameters are, and the smaller the other parameters will be. For the 2nd order Gauss-MRF, parameter B1,B2 of tangential texture are smaller than that of radial texture, while B3 and B4 of tangential texture are greater than that of radial texture, respectively. Therefore it can be used as the basis to classify radial texture and tangential texture. As for the automatic classification of wood textures, the 5th Gauss-MRFparameters were used as the feature vectors in the classification, with correctness ratio being 88% as a whole, well satisfying the requirement for automatic computer classification.

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